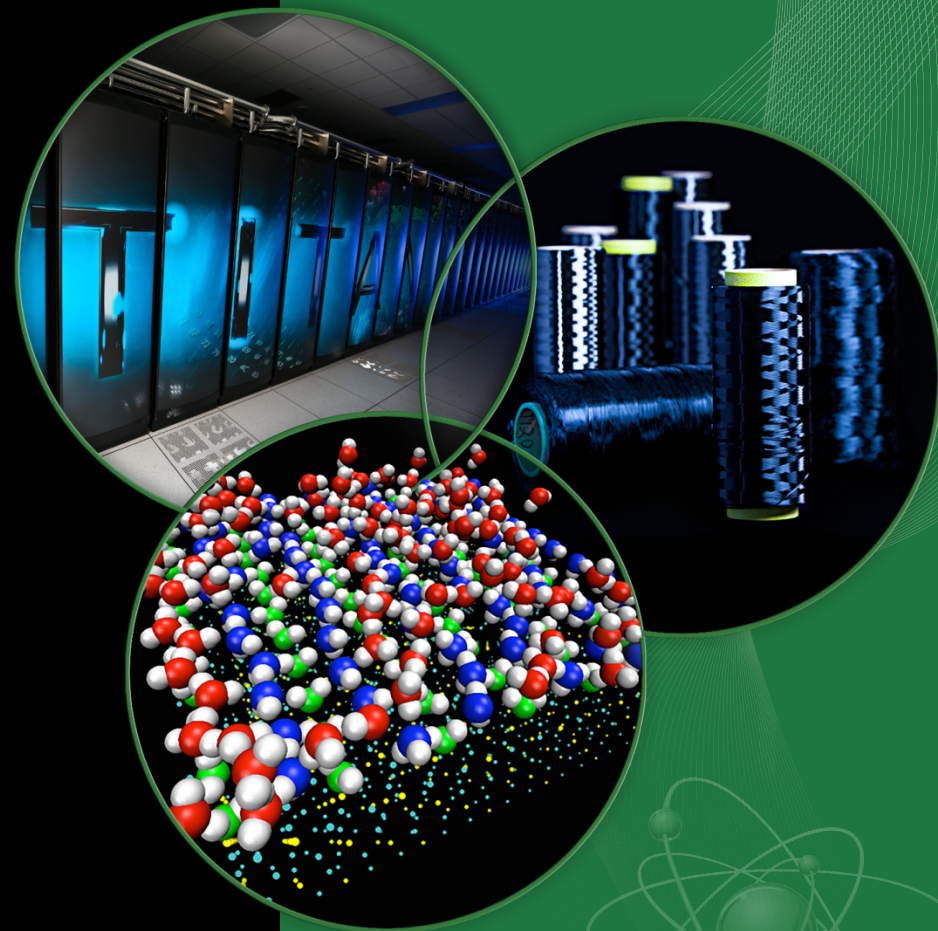


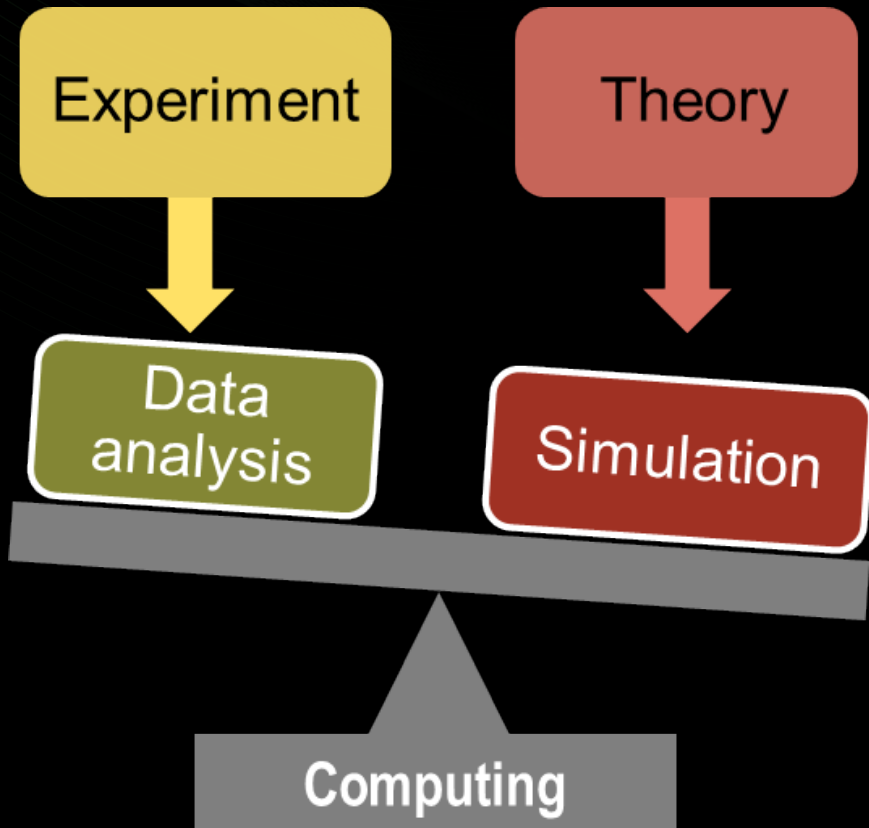
The OLCF “Data Group”

Sreenivas “Rangan” Sukumar

Data Scientist and Group Leader
National Center for Computational Sciences
Oak Ridge Leadership Computing Facility



Group Mission and Vision



Mission:

Design and build creative solutions for data-driven discovery in science domains at scale and performance using diverse compute architectures.

Vision:

On-Demand Data, Analytics and Workflows

Group Future : Scientific Data Facility

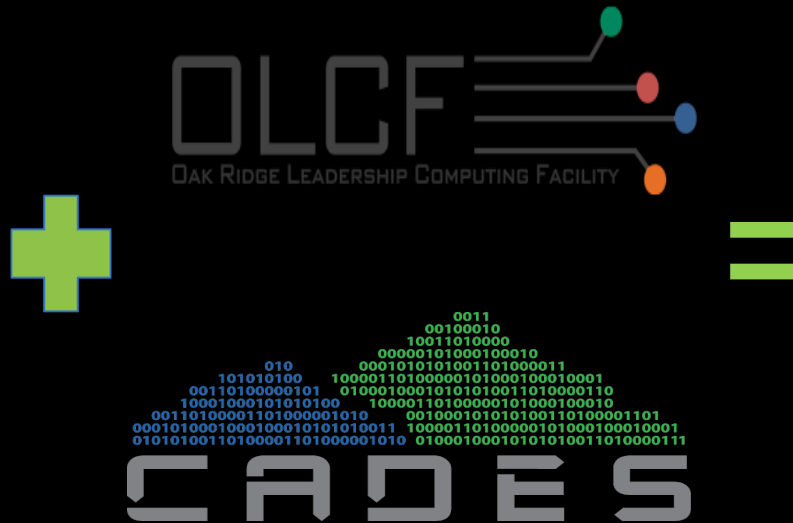
Spallation Neutron Source



Center for Nanophase Material Sciences



Manufacturing Demonstration Facility



Facilities of the future

The “Data” Group : People



Admin: Jessica West

Data Science Liaisons

Rangan Sukumar

John Harney

Valentine Anantharaj

Scott Klasky (M)

George Ostrouchov (M)

Visualization Liaisons

Mike Matheson

Jamison Daniel

Benjamin Hernandez-Arreguin

Kat Engstrom

David Pugmire (M)

Production/Software

Dale Stansberry

Brian Smith

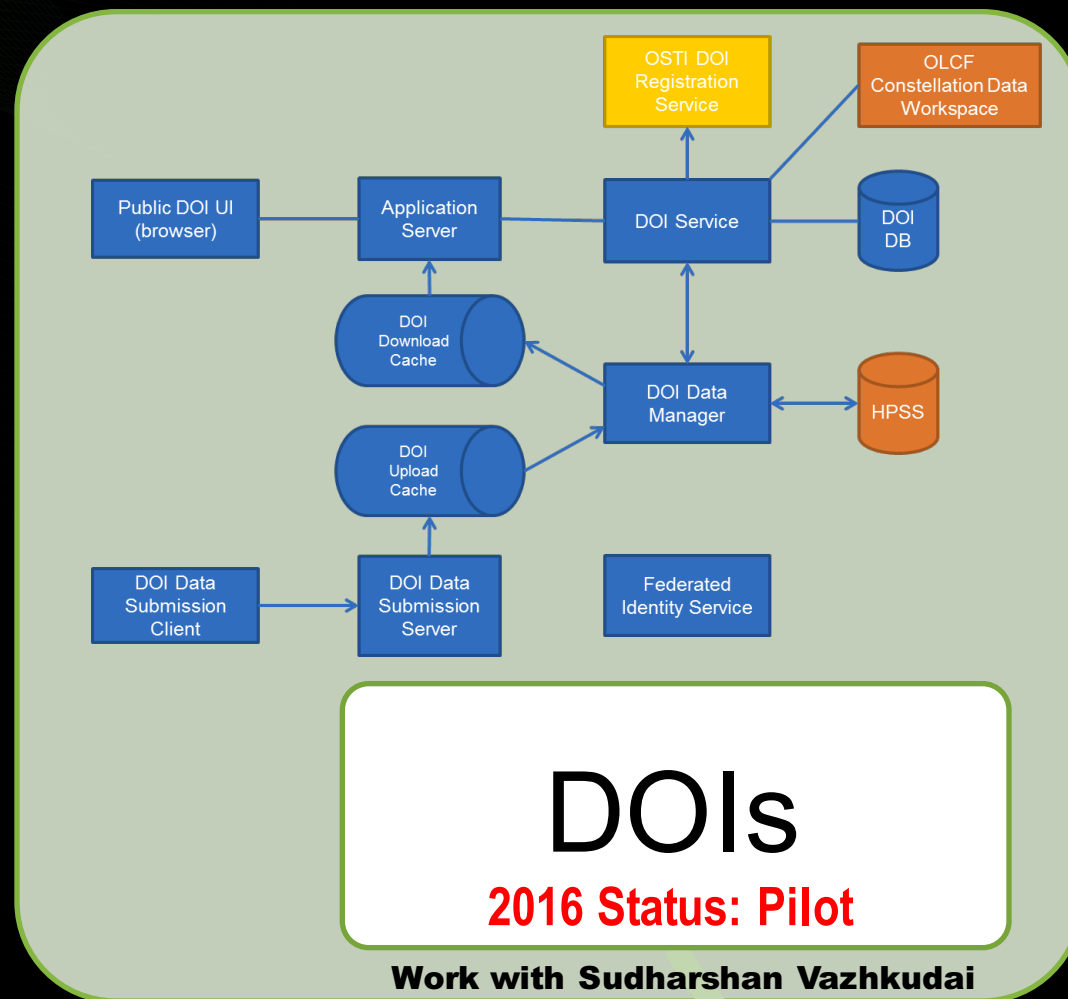
Norbert Podhroszki (M)

We need your help.

Survey Link:

<http://goo.gl/QCit1z>

Roadmap: On-Demand Data



Data Portals

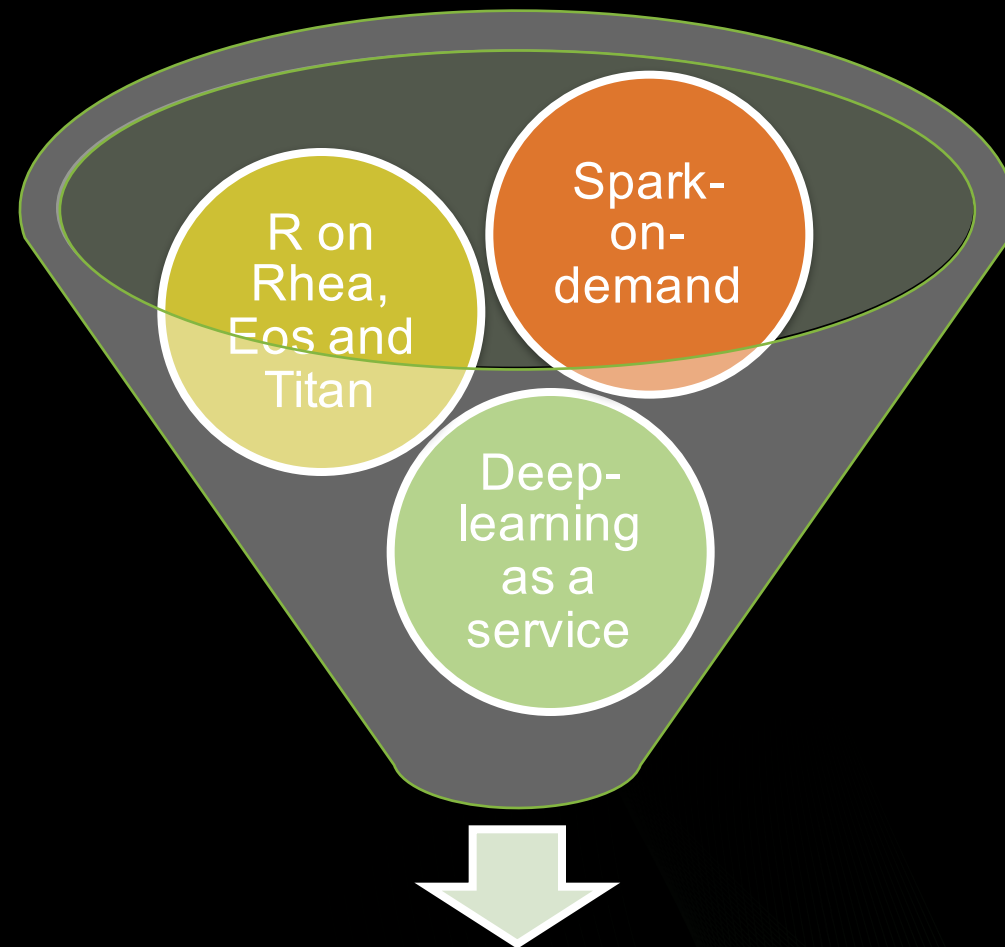
Peta-byte scale
“Github” for
Scientific Data

Collaboration with Technology Integration
Group @ OLCF, OSTI and CADES

Roadmap: On-Demand Analytics

2016: Mini-Apps for Big Data

Kernel	Mathematical Form	Algorithms
Least Squares	$\sum XX^T$	PCA, ICA, Naïve Bayes, Linear Regression, Logistic Regression
Convolution	$\int f(s)a^{st}dt$	Fourier, wavelet, z-transforms, deep learning, blind separation, image reconstruction
Distance	$ X_i - X_j ^k$	Covariance matrix, ray-tracing, k-means, k-NN
Matrix Decomposition	$\min_{w \geq 0, H \geq 0} \ X - WH\ _F^2$	Recommender systems, Spatiotemporal data mining, signal processing
Optimization	$X^{t+1} \rightarrow \alpha P X^t + (1 - \alpha)g$	Label propagation, iterative optimization
Sequence processing	$lev_{a,b}(i,j) = \begin{cases} \max(i,j) & \text{if } \min(i,j) = 0 \\ \min \begin{cases} lev_{a,b}(i-1,j) + 1 \\ lev_{a,b}(i,j-1) + 1 \\ lev_{a,b}(i-1,j-1) + 1 \end{cases} & \text{otherwise} \end{cases}$	Approximate text-search, sequence alignment problems
Graph-theoretic	$det(QAQ^T)$	N-ary search, pattern extraction



Architecture-Agnostic Analytic App-Store

Roadmap: On-Demand Workflows

2016: Testing Today's Tools



Eos 2.0 ?

Workflow Infrastructure

Federated ID
Management

Certificate
Management

Pilot Job
Launcher

Resource
Manager

Data-
Transfer

Workflow
State
Tracker

HPC

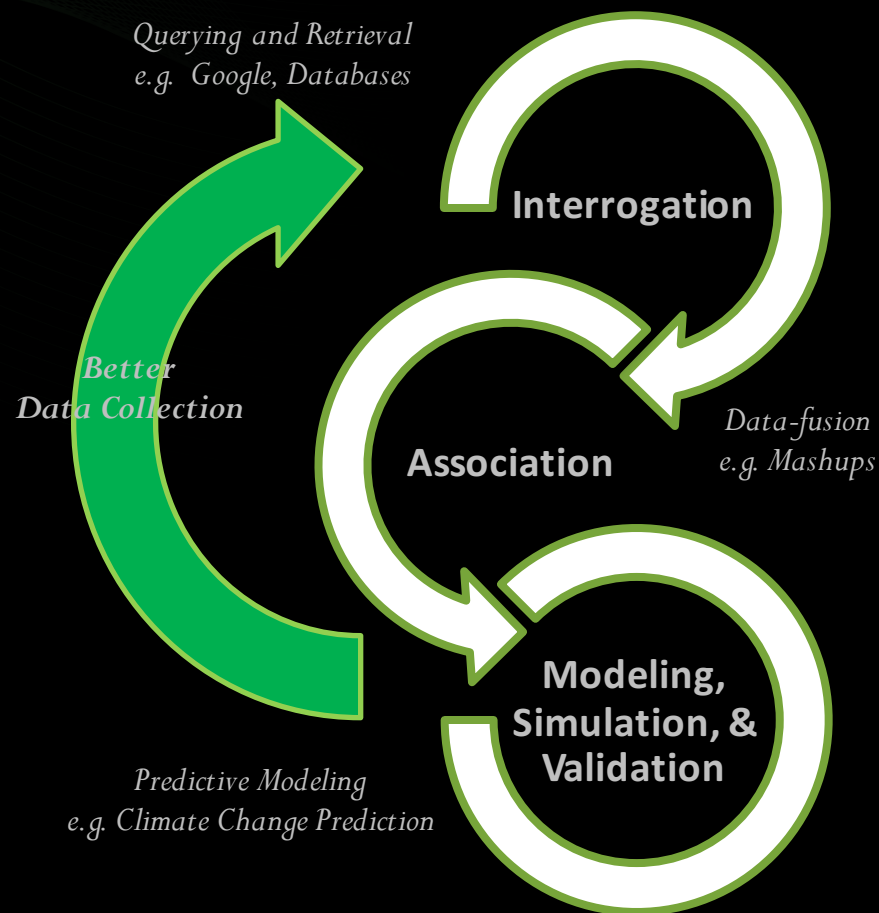
Streaming
(FPGA)

Globus
endpoints

Graph

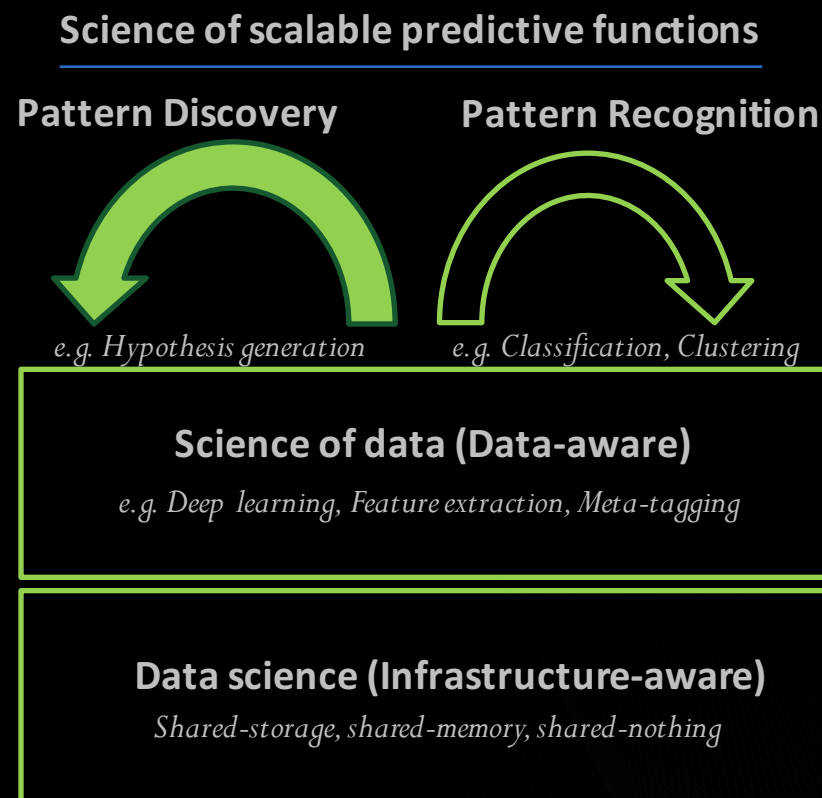
What have we started doing ? Data Science Support

The Lifecycle of Data-Driven Discovery



Domain Scientist's View

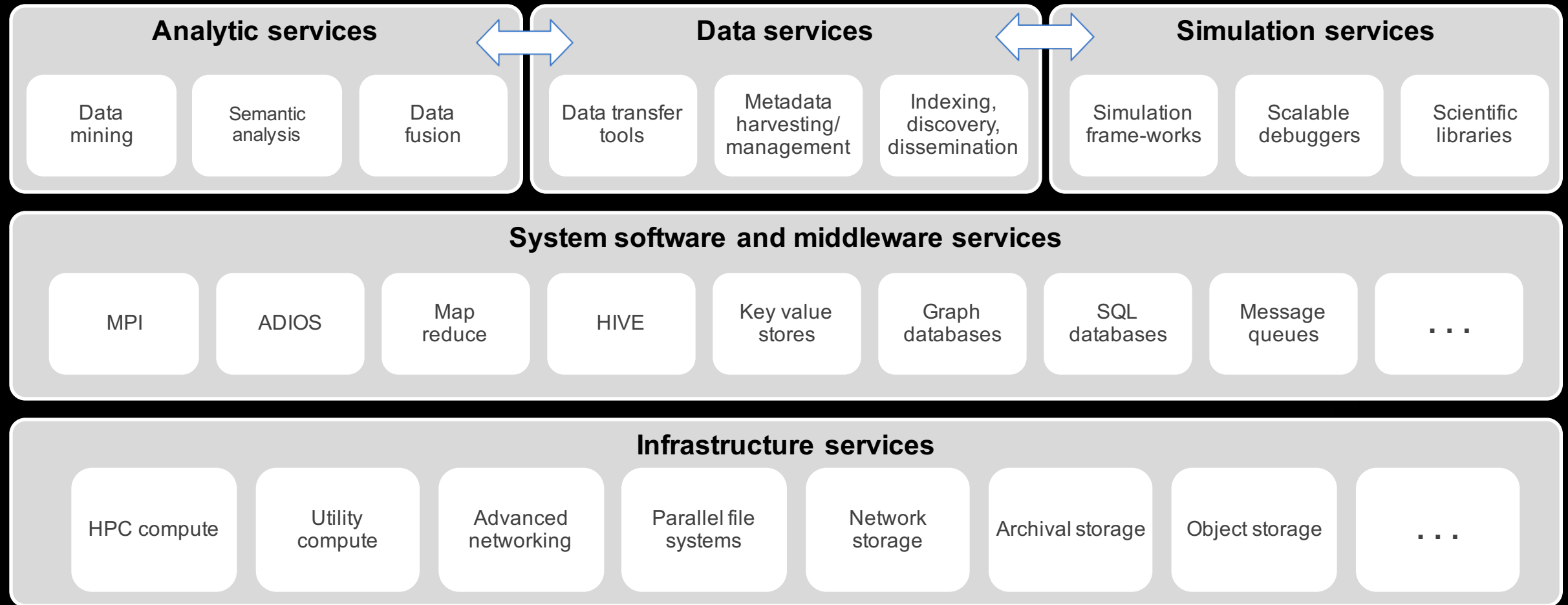
The Process of Data-Driven Discovery



Data Scientist's View

Building Knowledge Discovery Ecosystems

What have we started doing ? Data Science Support



Integrate with Compute and Data Environment for Science

What are we learning ? Science vs. Industry

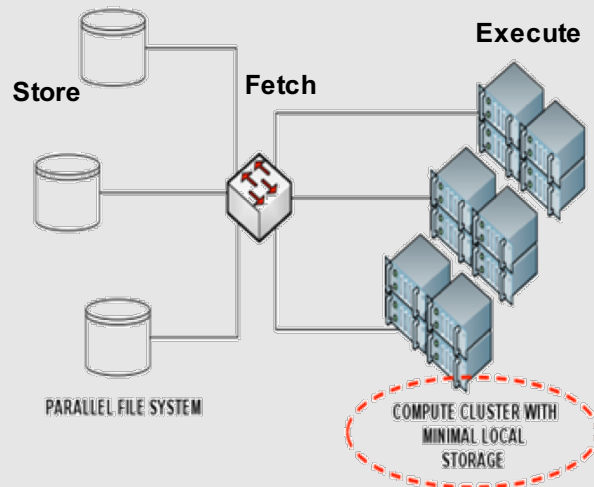
Big Data	Science	Industry
Data (Structured)	Vector, Matrix, Tensor	Table, Key-Values, Objects
Data (Unstructured)	Mesh, Images (Physics-based)	Documents, Images (Camera)
Visualization	Voxel, Surface, Point Clouds	Word Cloud, Parallel Co-ordinates, BI Tools
Validation	Cross-validation (ROC curves, statistical significance)	Manual / Subject matter expert, A/B testing
Extract, Transform, Load	Fourier, Wavelet, Laplace, etc. Cartesian, Radial, Toroidal, etc.	File-format transformations e.g. CSV to VRML
Search (Query)	Properties such as periodicity, self-similarity, anomaly, etc.	SQL, SPARQL, etc. (Sum, Average, Groupby)
Funding Model	Non-profit grand challenge (Answer matters)	Value-driven (Cost matters)

What are we learning ? : HPC vs. Big Data

HPC: Forward Problem

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi ux} dx$$

$$HPC : f(x) = \sin(x)$$



- Data analysis algorithms are designed for functionality. Scaling and performance is an afterthought.
- Speed-up and scale-up are a function of architecture, data characteristics and algorithmic-workflow (as viewed from the Amdahl's law perspective).

Big Data: Inverse Problem

Latency	Real-time (with interactivity)
Expectation	Batch (response time not critical)
Access Pattern	Random (unpredictable access) Sequential (list-like access) Permutation (data is moved re-distributed often)
Working Set	All Partial Iterative
Data Type	Structured (tables, matrices) Unstructured (text, binary files) Media (images, video)
i/o profile	Read-heavy (loading data to memory) Write-heavy (large intermediate result sets)
Complexity	Low (data access with small compute operations) Medium High (data and compute intensive operations)

Different algorithms have different workload patterns

What are we learning ?

- Either, invest in customized hardware that are expensive (\$1-10 M) and will NOT allow popular open-source/commercial software tools.
- Or, implement scalable theory-inspired algorithms on commodity or HPC clusters which in general takes a lot of effort without performance guarantees.



Massively parallel processing databases



“Analytics is retrieval”

Distributed Analytics on Storage



“Take compute to cheap storage”

Distributed-memory Analytics



“Algorithm is made to work on distributed memory-chunks”

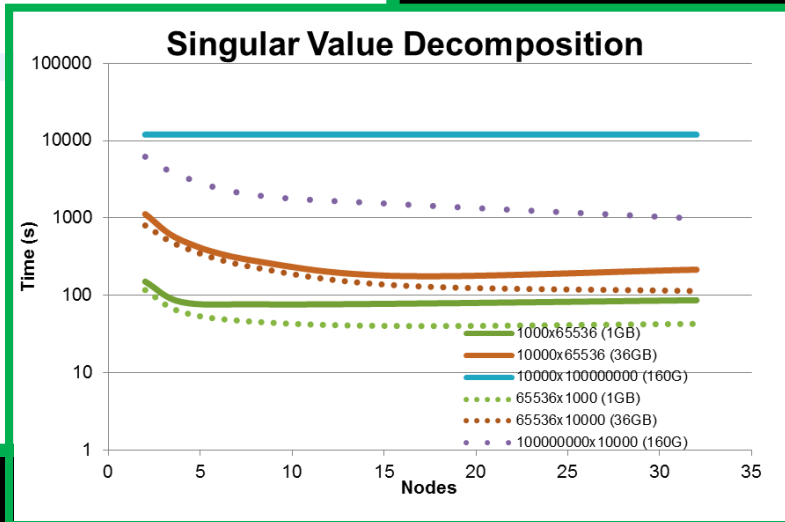
How are we solving some of these challenges ?

Apache Spark on Demand

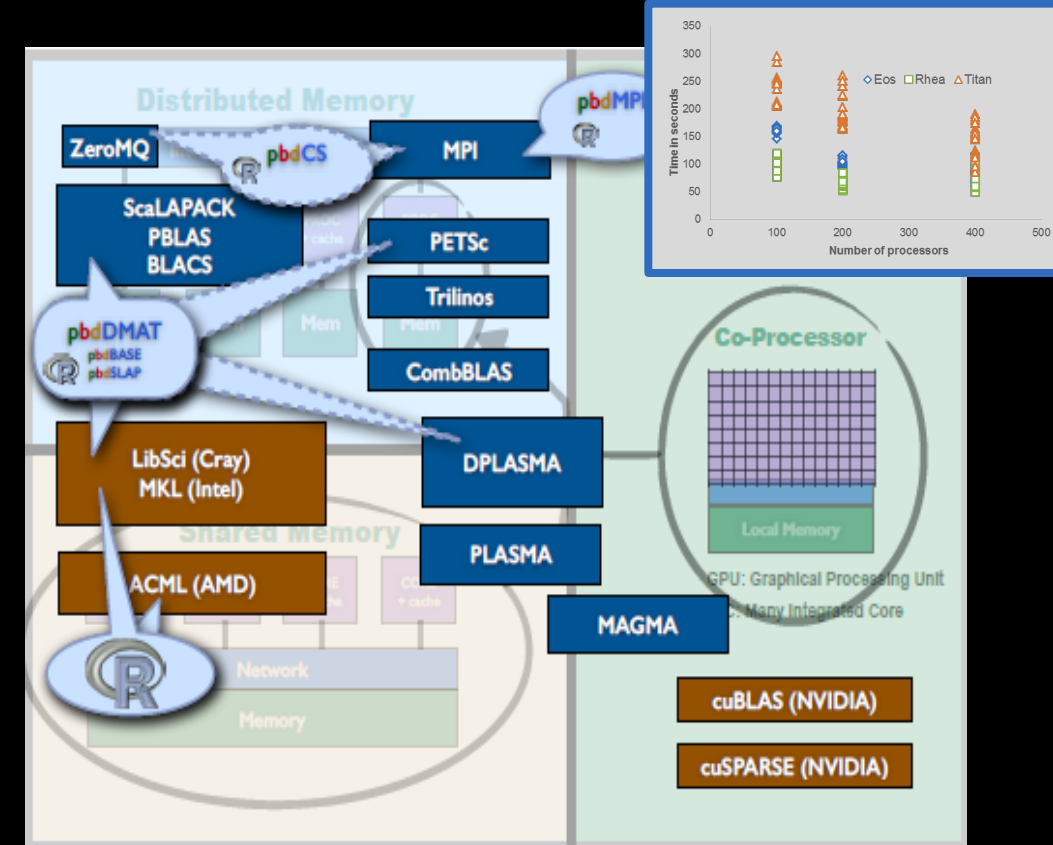
```
object SVD {  
  def main(args: Array[String]) {  
    if (args.length != 1) {  
      System.err.println("Usage: SVD <input>")  
      System.exit(1)  
    }  
  
    // Spark context  
    val conf = new SparkConf().setAppName("SVD")  
    val sc = new SparkContext(conf)  
  
    // Load and parse the data file.  
    val rows = sc.textFile(args(0)).map { line =>  
      val values = line.split(' ').map(_.toDouble)  
      Vectors.dense(values)  
    }  
    rows.cache()  
    val mat = new RowMatrix(rows)  
  
    // Compute SVD.  
    val svd = mat.computeSVD(50)  
  
    // Relevant Output  
    val singular = svd.s  
    val u = svd.U  
    val v = svd.V  
  
    sc.stop()  
  }  
}
```

Work with Seung-Hwan Lim

Spark now runs
on Rhea



R on Rhea, Eos and Titan



Work with George Ostrouchov

**Tutorial and demos presented on Day 0 sessions
and will be available on the OLCF website**

What have we started doing ? Visualization Support

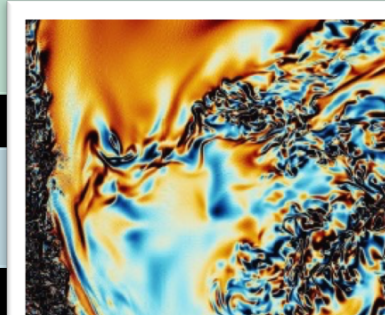
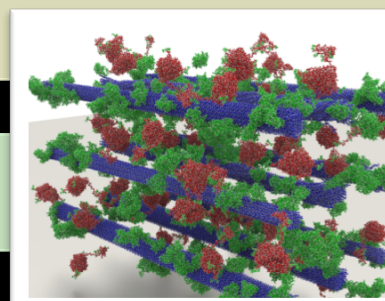
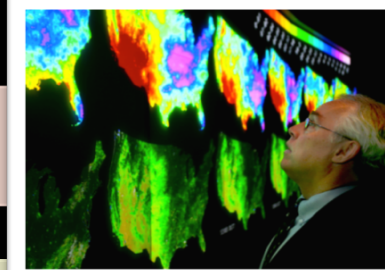
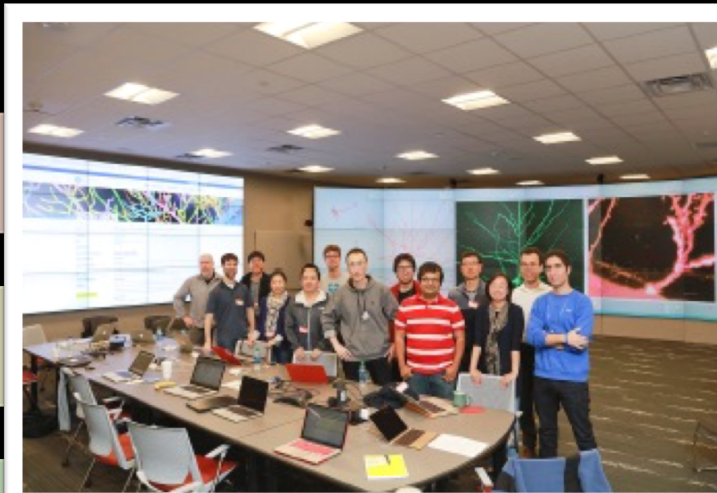
General Visualization Tools: VisIt, Paraview, Ensight, NICE DCV

Domain Visualization Tools: VMD, vaa3d, vapor

Libraries: ADIOS, OpenGL, OptiX

Rendering Tools: Maya, Unity, Blender, Custom

Hardware: Everest, Titan GPUs



What are we learning ?

Oculus Rift



HoloLens



Personalized
Visualization

Remote
Visualization

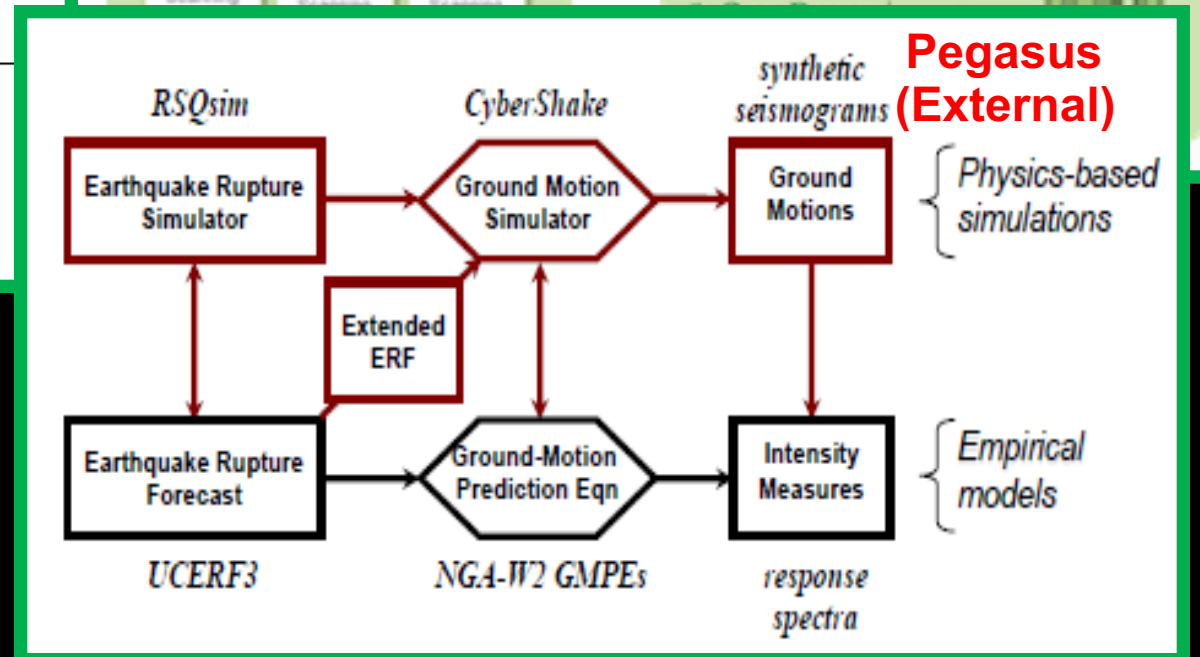
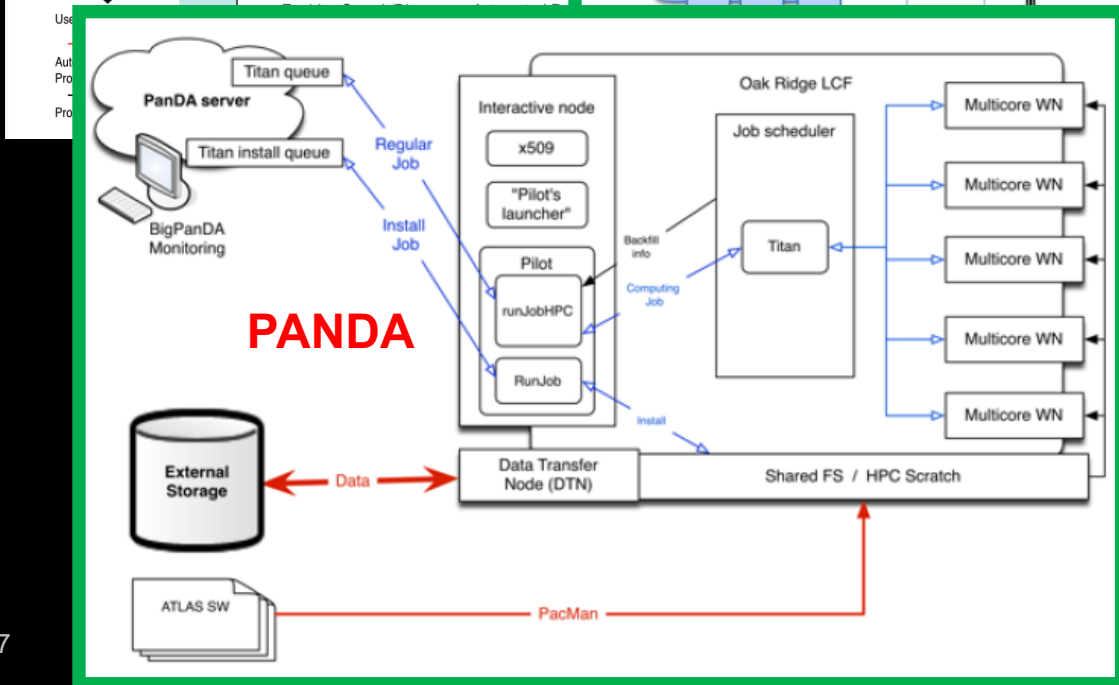
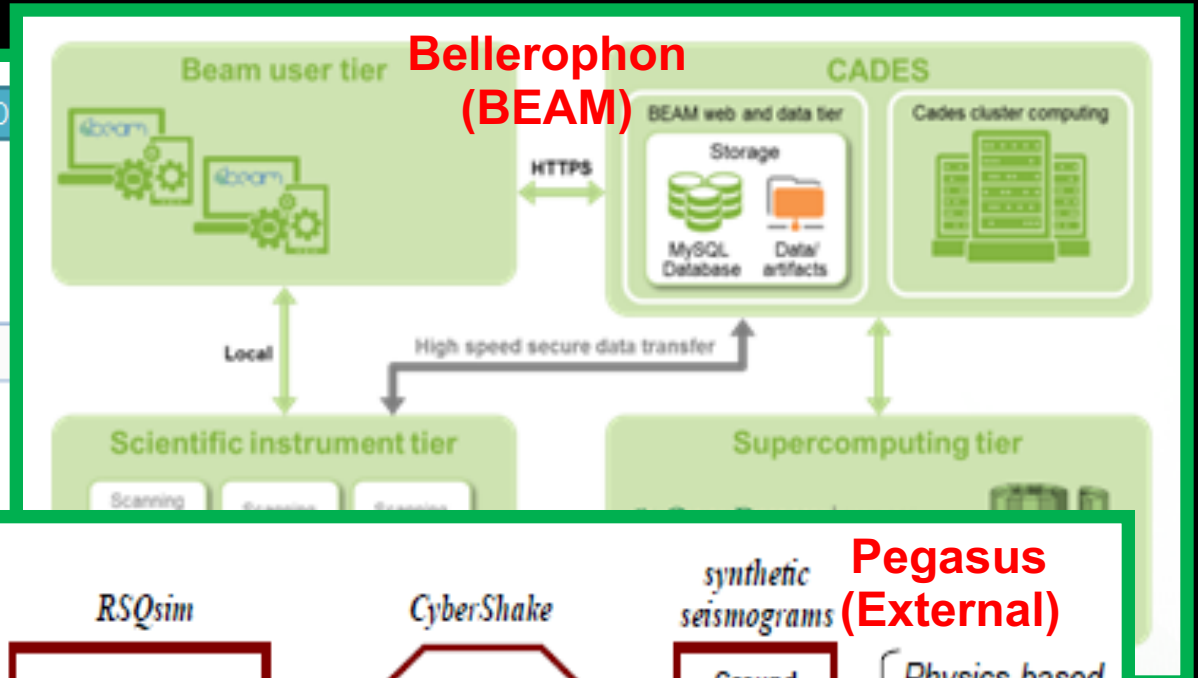
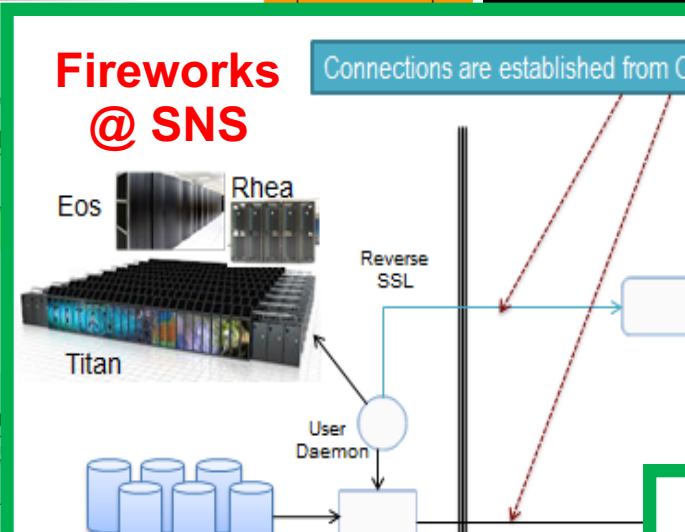
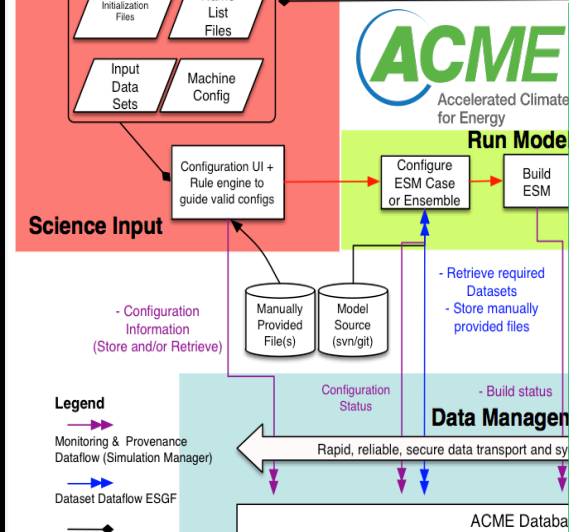
Power-Wall
Visualization

EVEREST@OLCF

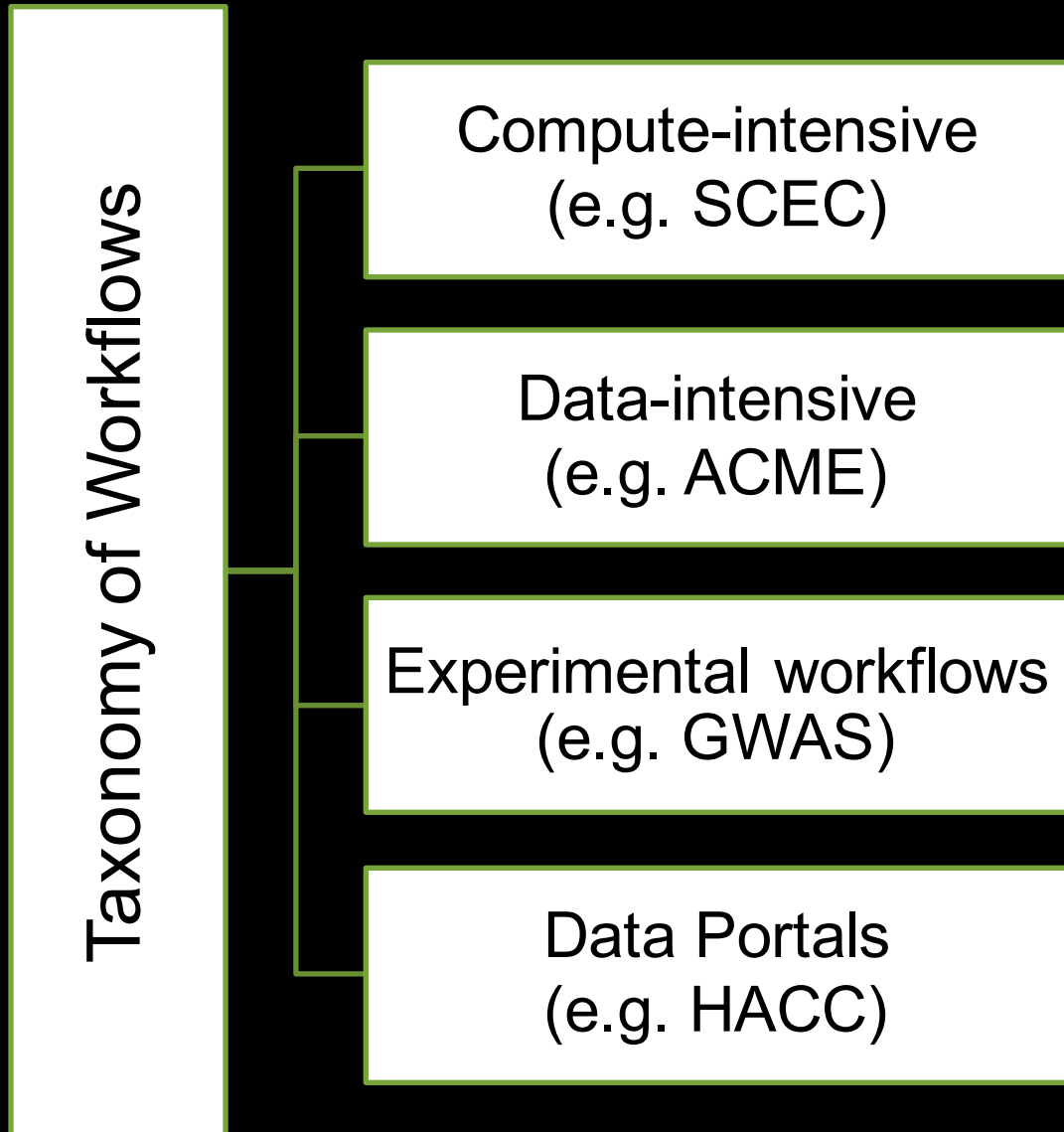


What have we started doing ? Workflow Support

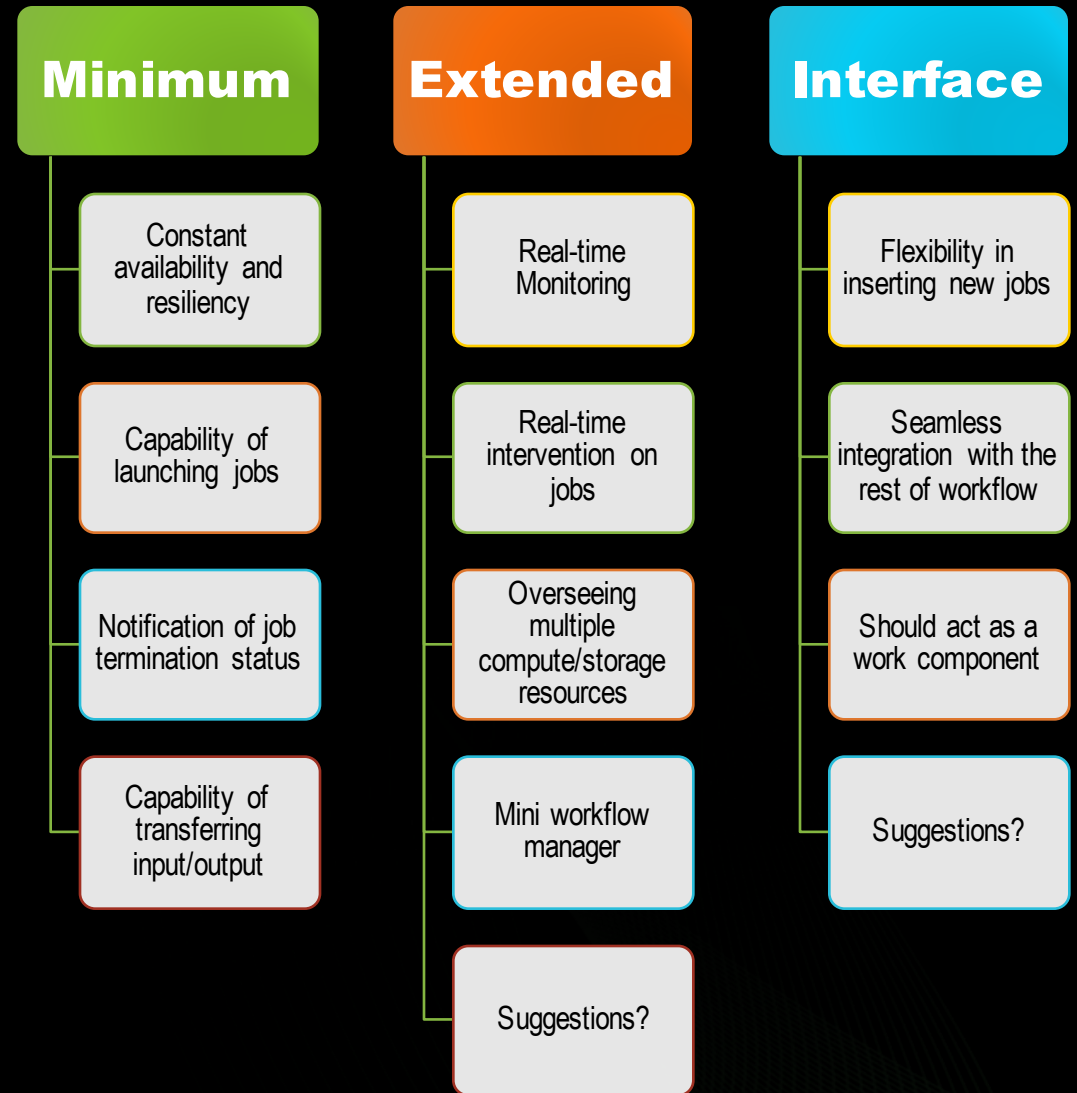
Pegasus (Internal)



What are we learning ?



Work with Byung Park



User Stories

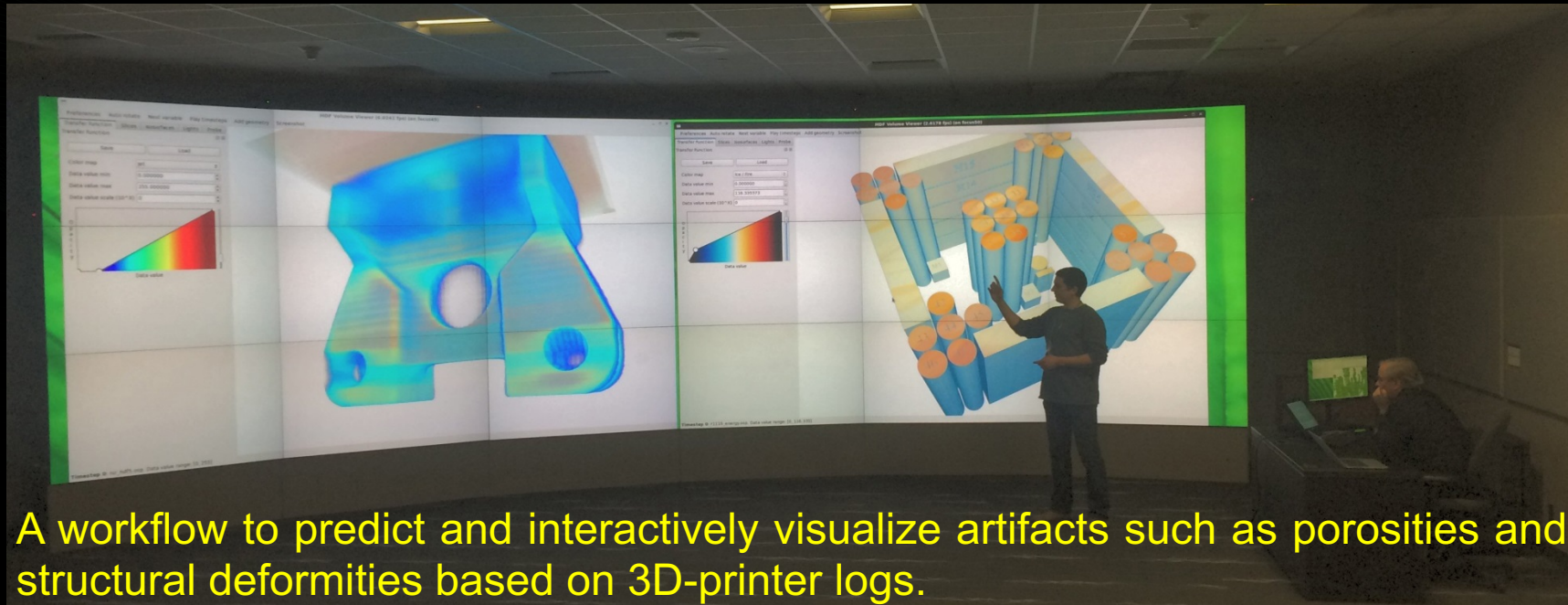
Use Case: Big Neuron Hackathon



Ran simulations on Titan and evaluated state-of-the-art neuron reconstruction methods on EVEREST. (Over 100 TBs of image data processed and analyzed in 3 days)

Attendees representing 13 organizations representing North America, Australia and Asia (INCF, OECD) in government and the private sector – Allen Institute for Brain Sciences, George Mason University, etc.

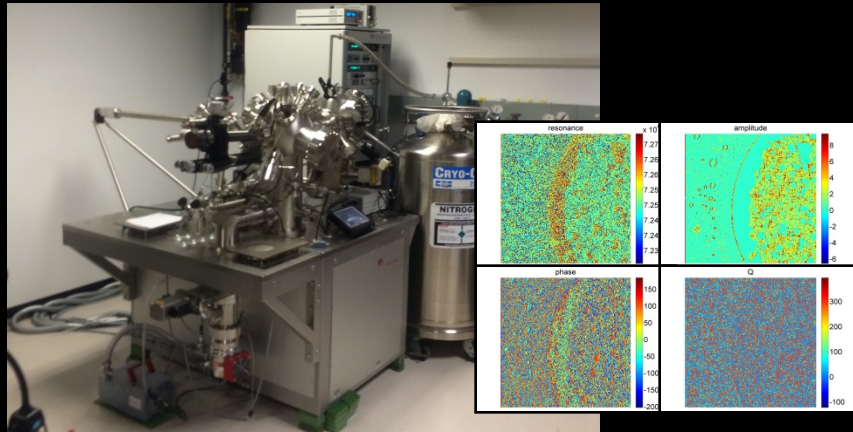
Use Case: Manufacturing Demonstration Facility



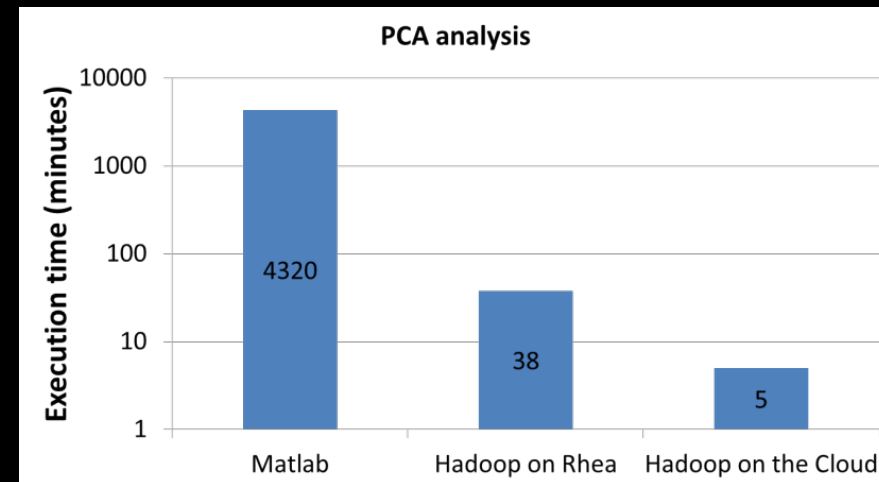
Use Case: Center for Nanophase Materials

How a data scientist can help the domain scientist ?

Scale-up: Instrument captures 1024 by 1024 image at 16000 different spectral bands



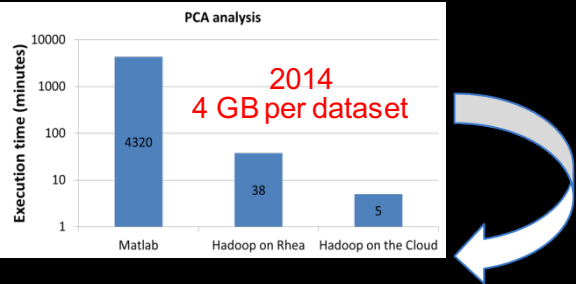
Speed-up: Principal component analysis of the image sequence



Given a data analysis algorithm of interest to a domain scientist, we can

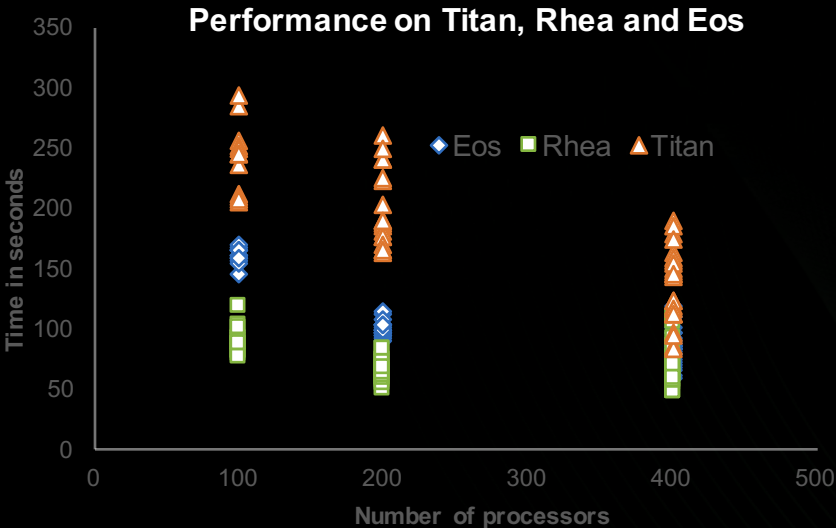
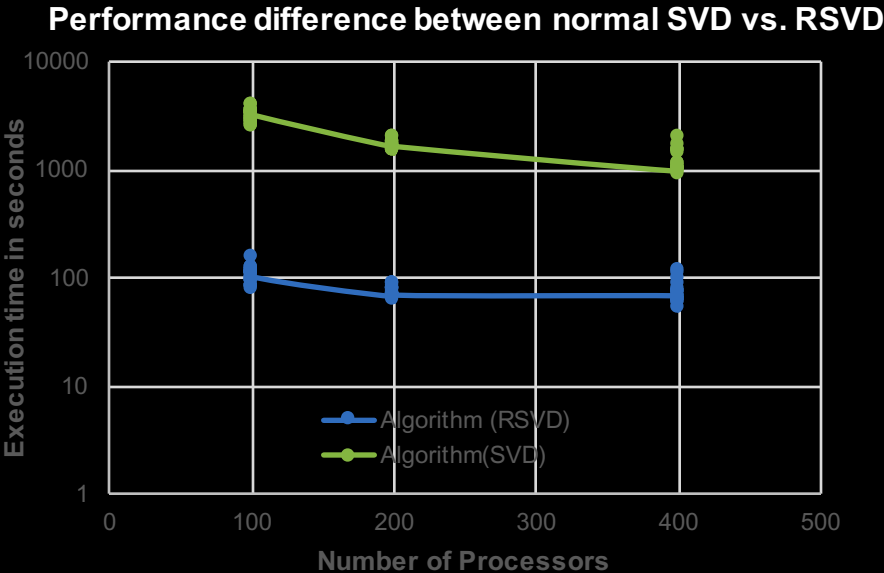
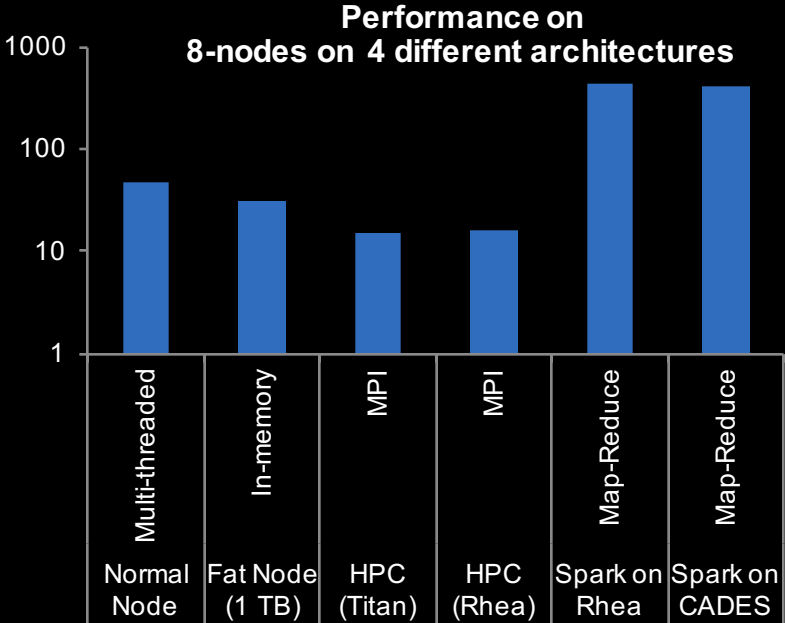
- recommend optimal 'analytic' architecture for speed-up and scale-up.
- quantify performance (cost and latency) trade-offs while using accessible instead of optimal hardware.

Use Case: Center for Nanophase Materials



2016: 134 GB per dataset

# of Cores	Speed-up		Execution time (seconds)	
	Fat-node	Rhea	Fat-node	Rhea
1	1.00x	1.00x	2747	4188
2	1.65x	1.75x	1663	2396
4	2.46x	2.87x	1117	1459
8	2.96x	3.65x	928	1146



Thank You... Questions ?

- How can we help you ? Please chat with our members when you get a chance.....
 - Collect surveys.....

How are we helping our science users ?



- **What hardware to buy/use ?**
 - Investment \$
 - Technology
 - Flexibility for growth
- **What is the cost of performance ?**
 - Portability
 - Energy
 - Time-to solution